

Research

Optimized deep learning models for stress-based stroke prediction from EEG signals

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Abstract

In this research, the use of non-invasive electrode-based EEG (electroencephalogram) signal measurement as a means to detect emotional and stress-related factors in individuals, is explored. This research focuses on evaluating EEG signals, particularly those channels that provide insights into motor-related brain activity, cognitive processes, and visual perception and processing. These have attracted interest in the context of predicting diseases. By integrating stress and disease prediction into a single module, this approach aims to offer an early warning system for individuals, enabling them to mitigate or avoid future health risks. Chronic stress is known to have hazardous effects on health, potentially triggering inflammatory responses within the body. These responses are linked to an elevated risk of cardiovascular diseases, which, in turn, can heighten the risk of stroke. The proposed research aims to classify stress-induced emotions and predict stroke risk using advanced deep learning algorithms. The study utilizes EEG signals to categorize stress-related emotions, subsequently assessing stroke risk via an optimized deep learning model. The proposed model is distinguished by its optimized hybrid optimization technique for feature extraction, aimed at stress and stroke prediction. The classification of stress emotions is achieved through the application of a BiLSTM (Bidirectional Long Short-Term Memory) network, while the assessment of stroke risk is conducted using deep Q-learning. The effectiveness of the proposed model is validated through experiments conducted with the benched mark DEAP dataset, demonstrating its robust performance in both stress and stroke prediction.

Article Highlights

1. *Early stroke risk detection:* The study links stress patterns in brain signals to potential stroke risks for early intervention.
2. *Smart AI-based prediction:* A deep learning model analyzes brain activity to classify stress levels and predict stroke likelihood.
3. *Enhanced accuracy & insights:* The model outperforms traditional methods, offering better accuracy in stress and stroke prediction.

Keywords Stress analysis · Stroke prediction · Deep learning · Hybrid optimization · EEG data

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1 Introduction

The innovation of EEG supports the assessment of brain function in clinical and research applications. Different frequency bands of EEG signals are utilized in medical applications to detect health disorders. The EEG signals have frequency ranges delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (16–31 Hz), and gamma (36–90 Hz) [1]. Each frequency band provides different features, specifically the delta band associated with deep sleep, unconsciousness, and neurological disorders. Theta band is associated with cognitive processes, memory, and attention. The Alpha band associates with the changes in arousal and attention. Beta band is associated with motor functions, sensory processing, and active cognition. The gamma band is associated with higher cognitive processes such as perception, memory, and consciousness. Changes in these frequency bands affect the process mentioned above, and by observing these changes through EEG signals, health issues can be detected with high precision. Figure 1 visualizes the various EEG frequency bands.

Stress is a crucial factor in the fast-moving world. People experience stress factors in any situation, and it is different for each person. Stress is a sense of emotional tension that occurs due to pressure, challenging situations, or simply worry that can lead to stress. Stress in the human body affects human health [2]. An autonomic nervous system is activated due to mental stress. One of the common brain stress disorders is Alzheimer's [3]. Identifying stress is essential, and the research community provides various methods to identify stress. Magnetic resonance imaging, computed tomography, and EEG are used to identify stress. Among all, EEG provides significant results as it directly reflects the electrical activity of the human brain through the electrodes placed in the head. The non-invasive procedure collects feedback from stress hormones and is a reliable tool for stress measurement. Stress analysis can define the relevance of heart rate variability to hemodynamics [4]. Continuous stress factors in humans can increase the probability of further health issues like stroke, heart disease, etc. Stress factors can be used to predict future health issues. In this view, a novel stress-based stroke prediction model is presented in this research work. The research aims to detect stress and predict strokes based on the optimal features of the EEG signals. To attain the above objective, the contributions made in this research work are given as follows.

- **Preservation of Raw EEG Information:** The proposed methodology begins with raw EEG data, which is preprocessed to retain the richness and variability inherent in the signals, ensuring that no valuable information is lost at this stage.
- **Hybrid Feature Extraction Framework:** Contrary to solely relying on raw data, the model employs the hybrid Zebra-Chimp Optimization (ZCO) algorithm to extract the most relevant time and frequency domain features. This process balances the complexity of raw EEG data with the need for dimensionality reduction, enhancing the performance of downstream deep learning models.
- **Integrated Deep Learning Models:** The extracted features are fed into a Bidirectional Long Short-Term Memory (BiLSTM) network for stress emotion classification and a Deep Q-Network (DQN) for stroke prediction, leveraging the optimized feature set for accurate and reliable outcomes.

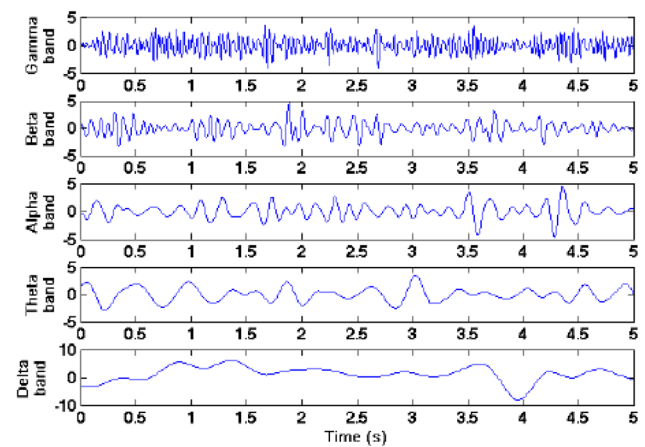
The remaining discussions are arranged in the following order. The literature review given in Sect. 2 provides a brief overview of different stress and stroke analysis models. The proposed stress-based stroke prediction model is presented in Sect. 3. Section 4 provides the results and discussion. The findings are in Sect. 5.

2 Related works

Research towards stress analysis and its related medical diagnosis based on EEG signal has been quite popular over a decade. Some of the recent research works are considered for literature analysis and the observations are presented in this section. Different machine learning and deep learning models are used for stress and stroke prediction [5]. An EEG based stress level analysis model presented in [6] classifies different levels of stress using learning algorithms. The presented CNN based stress analysis model extracts the stress features from the EEG signal and compares the performance with traditional machine learning algorithms like support vector machine and multilayer perceptron. Experimental results confirm that the CNN based stress analysis attained better accuracy compared to traditional learning algorithms.

The impacts of stress in psychological and behavioral disorders are studied in [7] and presented a correlation analysis between EEG and heart rate variability. The changes in stress level and its aftereffects are analyzed by observing the heart rate variability in EEG signals. The experimental analysis extracts the low and high frequency features from EEG

Fig. 1 EEG frequency band visualization [Source: Zahad et al. 2015]



signal along with root mean square of successive difference (rMSSD) to improve the stress detection performances. The machine learning based mental stress detection procedure presented in [8] extracts the complex features of EEG signal of different subjects. Initially multivariate multiscale entropy method is used in the proposed model to characterize the non-linear time series data. Then the resting and cognitive workload condition brain EEG signals are analyzed to identify the stress factors. Finally using SVM the stress factors are classified and attained better classification accuracy than other machine learning models.

The machine learning based stress analysis model presented in [9] extracts essential features from EEG signal using principal component analysis and classifiers. The experimental procedure utilizes electrodes on different count and measured the machine learning performances. The experiments present that the data acquired using two electrodes provides better classification accuracy than others. However, in practical scenario and person characteristics, the presented model performance is average, and it can be improved further for better detection performances. The combination of particle swarm optimization and SVM for mental stress recognition is presented in [10]. The presented model extracts the optimal features using redundancy relevancy with particle swarm optimization and classifies them using SVM. Experimentation utilizes a four benched mark dataset, and the presented model attained an average of 70% recognition accuracy which indicates that the recognition model requires better feature extraction and classification procedures to attain better recognition performances.

An EEG based mental stress analysis model presented in [11] initially transforms the time domain data into frequency domain data using FFT. Then the features like normalized power peak, relative power, absolute power and change in power are extracted using the t-test feature selection procedure. Finally, a confidence score is provided for all the features and based on the normal and stress classes are defined. Though the stress analysis procedure is simple it requires a detailed domain knowledge to categorize the normal and stress classes based on confidence score. The stress classification model presented in [12] decomposes the EEG signals into different frequency bands using discrete wavelet transformation. The class imbalance in the data samples is balanced through adaptive synthetic sampling. Then using affinity propagation with artificial neural network, the samples are classified to define human emotions. Experiments using benchmark dataset reveal that the performance of affinity propagation with ANN is better than affinity propagation with SVM and Random Forest models. An ensemble model presented for stress classification [13] includes discrete wavelet transform to decompose the frequency bands in EEG signal. Then using a combination of statistical importance, the features are extracted. Finally using the ensemble model which includes linear discriminant analysis, extra tree, extreme gradient boosting algorithms classifies the features with better classification accuracy.

The deep learning based mental stress classification model presented in [14] comparatively analyzed the performance of recurrent neural network and several machine learning classifiers. The experimental observation confirms that the performance of the recurrent neural network is better in identifying the stress level over machine learning algorithms. The deep learning-based stress analysis model presented in [15] includes a compact CNN for feature extraction from EEG signal. The presented CNN model extracts the features and classifies with better accuracy than machine learning algorithms and the experiments found that frontal and temporal band signals are more prominent features which clearly indicate the stress factors. The stress analysis procedure presented in [16] utilizes a three-dimensional CNN model with an attention mechanism [17, 18] to attain improved classification performances. The presented model decomposes the EEG signal into different frequency bands and captures the prominent features through gated self-attention mechanism.

Then using frequency mapping, the complementary features are learned from different frequency bands to reflect the stress factors.

The stroke detection model presented in [19] extracts the frequency bands from EEG signals using discrete wavelet packet transform and utilizes their non-linear classifiers like random forest, probabilistic neural network and k-NN to classify them to define the emotional impairments. Experiments reveal that the people who have damaged their left brain have a high probability of getting a stroke. Among all three classifiers, random forest detects better than others with better classification rate. The machine learning based stroke detection procedure presented in [20] incorporates k-NN, SVM and random forest classifiers for detecting stroke patterns from EEG signals. The presented model initially retrieves the features through statistical analysis and then included Laplacian eigenmap to reduce the feature dimensions. Finally using machine learning classifiers, the performances are comparatively analyzed and observed that random forest outperformed other algorithms with better accuracy. However, the obtained 74% accuracy should be improved further to provide accurate stroke detection.

The stroke classification model presented in [21] utilizes machine learning algorithms like SVM, k-NN and random forest algorithms to classify the features in EEG signal. In the presented model, using wavelet transform and independent component analysis, the frequency bands are decomposed, and the dimensions are reduced. Further the features are extracted and classified using machine learning algorithms. Experimental results depict that the random forest has better classification accuracy in stress analysis over other machine learning algorithms.

Optimization algorithms are used for feature selection and extraction in various domains. In the EEG based stress and stroke detection procedure, optimization algorithms are used to select the optimal features from EEG signals. The stress classification model presented in [22] utilizes an optimization algorithm for selecting the optimal features from EEG signals. The presented classification model utilizes African vulture optimization technique for optimal feature extraction and then classify the features using modified Elman recurrent neural network. The experimentation results present that the classification model has attained better accuracy than traditional approaches.

The stress analysis model reported in [23] presents an improved particle swarm optimization algorithm to realize the stress factors present in the EEG signal. The presented approach initially filters and detects the EEG signal using wavelet transformation. Then using Improved PSO, the speed limits in signal are eliminated and realize the stress factors with better accuracy than conventional realization procedures. The EEG signal-based stress analysis model presented in [24] estimates the patient depression states using bat optimization based deep learning model. The necessary features in the EEG signal that causes depression are selected and extracted using bat optimization and then classified using U-Net deep learning model. Experimentation analysis validates that the performance of U-Net classifier is improved in detecting depression states due to the optimal features provided by the bat optimization algorithm.

The automatic seizure detection model presented in [25] extracts the multi-view features from EEG signals using particle swarm optimization algorithm and fed them to ML classifiers like SVM, random forest and k-NN models. Due to Multiview feature selection the classification performance of ML classifiers is improved and attained better detection accuracy over traditional approaches. The comparative analysis summarizes that PSO-SVM based seizure detection outperformed k-NN and random forest approaches. From the study it can be observed that machine learning models are widely used for stress analysis and most of the stroke detection models are based on deep learning techniques. The performances of existing stress classification models can be improved further if optimal features are selected from the EEG signals. Similarly for stroke prediction, features from the different frequency bands are used. However, none of the research work combined the stress and stroke prediction procedure. Thus, in this research work a novel procedure that combines stress-based stroke prediction is presented using hybrid optimized deep learning algorithm.

3 Proposed work

The proposed stress-based stroke prediction model is a three-phase work in which the optimal features from the EEG signals are extracted in the first phase using a hybrid optimization algorithm. Bio-inspired Zebra optimization and Chimp optimization algorithms are combined as a hybrid optimization algorithm to extract features related to stress and motor-related brain activities from EEG signals. In the second phase of research, stress-related emotions are classified using the deep learning BiLSTM model. In the third phase of research work, the possibilities of stroke are predicted using deep Q learning based on the extracted features and stress-related emotions. The process flow of the proposed work is presented in Fig. 2. The process starts with preprocessing the input data from the dataset. Further, the features are extracted from

the preprocessed dataset using a hybrid optimization algorithm and then classified to define the emotion states and predict the possibilities of stroke.

The preprocessing of the proposed model replaces the non-numeric terms with the average of all sample points and then utilizes a fifth-order Butterworth filter to filter out the necessary components related to stress and stroke prediction. The range of the filter is selected as 1–32 Hz, and it allows only the Delta, Theta, Alpha, and Beta frequency bands in the EEG signal. Then, z-score normalization is performed to reduce the signal instability and volatility. Mathematically, the normalization is formulated based on the mean and variance as follows.

$$x' = \frac{x - \mu}{\sqrt{\sigma^2}} \quad (1)$$

where the normalized EEG signal and filtered input data are indicated using x' and x respectively. The mean and variance are indicated using μ and σ . Further, the normalized data is split into different frequency bands to observe the features from the frequency bands of the EEG signal. These frequency bands are mainly divided to observe the micro variations in the signals, which is further used in stroke prediction. From the frequency bands, the time and frequency features are extracted using a hybrid optimization algorithm.

The hybrid optimization algorithm combines the zebra optimization algorithm with chimp's optimization algorithm. Based on the social behavior of zebras the optimization algorithm is formulated and in the proposed work based on the optimal solution of zebra chimp optimization the time and frequency domain features are extracted. The mathematical model has five phases in which creating a random group is the first phase. In the entire population S , the total number of groups N is calculated based on the stallion probability P as $N = S \times P$. The zebras are given as $z_{ij \in N} = \{z_{ij1}, z_{ij2}, \dots, z_{ijn}\}$ where n indicates the search space dimension and the position is given as $z_{ij} = (z_{max} - z_{min})rand + z_{min}$. Where z_{max} and

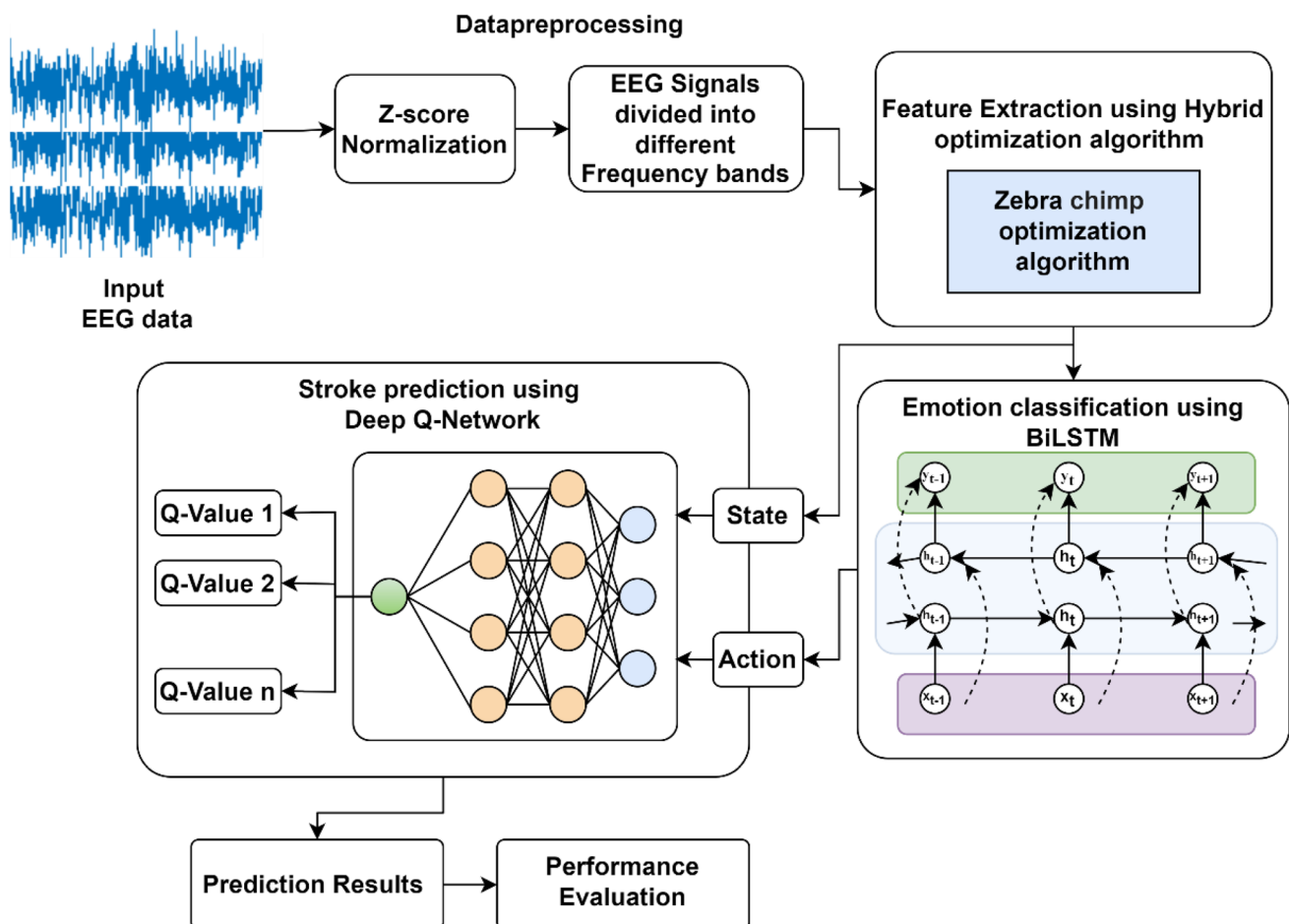


Fig. 2 Stress based stroke prediction using optimized deep learning techniques

z_{min} represents the lower and upper extreme points in search space and rand indicates the random value and its range is given as [0,1]. In the second phase, the feeding activity of zebras is formulated. The young zebras follow the family leader stallion and always graze together which is mathematically expressed as

$$z_i^j = \begin{cases} 2R_1 \sin(2\pi R_2) \times (z_s^j - z_i^j) + z_s^j & \text{if } R_3 < 0.5 \\ 2R_1 \cos(2\pi R_2) \times (z_s^j - z_i^j) + z_s^j & \text{otherwise} \end{cases} \quad (2)$$

where position of stallion and the position of zebra is indicated using z_s^j and z_i^j . The sin and cos functions define the movement of zebras in multiple angles. The range of uniform random value R_1 is given as [-2,2], R_3 is given as [0,1], and adaptive parameter R_2 is given as $R_2 = 1 - t \times \frac{1}{T}$, where current and maximum iteration is indicated using t and T .

The breeding activity of zebra is presented in the third phase of optimization model in which the zebra's crossover with zebras in other groups and produces new offsprings which is mathematically formulated as

$$z_j^a = \text{crossover}(z_i^a, z_j^b) \text{ if } r < pc, i \neq j \quad (3)$$

$$z_k^a = \text{crossover}(z_i^a, z_k^c) \text{ if } r \geq pc, i \neq k \quad (4)$$

where the position of zebra a from i^{th} group is given as z_i^a , similarly for j^{th} group is given as z_j^b , for k^{th} group is given as z_k^c . The crossover probability is given as pc . In the fourth phase, the leader of the family is defined as

$$\bar{z}_s^j = \begin{cases} 2R_4 \sin(2\pi R_5) \times (WR - z_s^j) + WR & \text{if } R_6 < 0.5 \\ 2R_4 \cos(2\pi R_5) \times (WR - z_s^j) + WR & \text{otherwise} \end{cases} \quad (5)$$

where the range of uniform random value R_4 is given as [-2,2], R_6 is given as [0,1] and the adaptive parameter R_5 is given as $R_5 = 1 - t \times (1/T)$. WR indicates the water reserves, and the current and next position of stallion is indicated using z_s^j and $\bar{z}_s^j$. In the last phase, the leader transition stage is formulated. If the current stallion is becoming weak due to age and other factors, then it is essential to select the new leader. This process mathematically expressed as

$$z_s^j = \begin{cases} z_i^j, & \text{if } F(z_i^j) < F(z_s^j) \forall i \in N_j \end{cases} \quad (6)$$

where z_s^j indicates the current position of leader stallion and $F(z_s^j)$ indicates the leader stallion fitness function. In the zebra optimization algorithm, the fitness function defines the next leader selection, and this parameter is optimized further using chimp optimization algorithm (COA). COA is a nature inspired optimization algorithm which is formulated based on hunting and sexual behavior of chimps. The optimization algorithm has four phases like driving, blocking, chasing, and attacking based on the four group of chimp's barrier, attacker, driver, and chaser. The hunting process of chimps has two main phases like driving and chasing as follows.

$$d = |cx_p(t) - mx_c(t)| \quad (7)$$

$$x_c(t+1) = x_p(t) - a.d \quad (8)$$

$$a = 2f.r_1 - f \quad (9)$$

$$c = 2.r_2 \quad (10)$$

where $x_p(t)$ is the prey position and chimp position are indicated using $x_c(t)$. The coefficient vectors are indicated as a , c and m . The dynamic vector f is given in the range [0, 2.5], the random vectors r_1 and r_2 range is given as [0,1]. The prey position is further calculated based on the four chimps as follows.

$$d_{att} = |c_1 \cdot x_{Att} - m_1 x| \quad (11)$$

$$d_{bar} = |c_2 \cdot x_{bar} - m_2 x| \quad (12)$$

$$d_{chas} = |c_3 \cdot x_{chas} - m_3 x| \quad (13)$$

$$d_{dri} = |c_4 \cdot x_{dri} - m_4 x| \quad (14)$$

$$x_1 = x_{Att} - a_1(d_{att}) \quad (15)$$

$$x_2 = x_{bar} - a_2(d_{bar}) \quad (16)$$

$$x_3 = x_{chas} - a_3(d_{chas}) \quad (17)$$

$$x_4 = x_{dri} - a_4(d_{dri}) \quad (18)$$

The updated position of each chimp is given as

$$x(t+1) = \frac{x_1 + x_2 + x_3 + x_4}{4} \quad (19)$$

where the best search agent is indicated as x_{Att} and the successive best search agent is given as x_{bar} , x_{chas} , and x_{dri} . $x(t+1)$ indicates the chimp updated position. Further using chaotic maps, the sexual movements of chimps are described as follows.

$$x_c(t+1) = \begin{cases} x_p(t) - a \cdot d & \text{if } v < 0.5 \\ \text{chaotic_value} & \text{if } v \geq 0.5 \end{cases} \quad (20)$$

where $x_c(t+1)$ indicates the chimp sexual movement, v is the random number and its range is given as $[0,1]$. The summarized pseudocode for the proposed hybrid optimization algorithm is given as follows.

Pseudocode for the hybrid zebra chaotic optimization algorithm

Input: Initialize zebras, crossover probability, stallion probability, chimp groups

Output: Optimal features from the EEG signal

Initialize population size and maximum number of iterations for optimization algorithm

Obtain the fitness function for each zebra

Determine stallion and other zebras

Initialize feeding phase and calculate the new position using equation (2)

Initialize breeding phase based on equation (3) and (4)

Group leadership and calculate the new position using equation (5)

Initialize the leadership transition and select new leader based on fitness function $F(Z_s^j)$

Optimize fitness function using chimp optimal solution

Initialize chimp and update the position based on equation (11)-(18)

Update the final position using equation (19)

Optimize the fitness $F(Z_s^j)$ using optimal solution of chimps

End all

End

The extracted features are then classified using Bidirectional LSTM network. The BiLSTM network is a time series data processing model which exhibits significant results by inferring from past to future and future to past. BiLSTM predicts labels for the current data based on past and future sequences. The information passes through the hidden layers in forward and

backward states in two separate paths. The final output is obtained by passing the input through both hidden layers and output layer. The forward and backward activation output of hidden layer is formulated in BiLSTM as follows.

$$\vec{h}_t = \sigma(w_{xh}x_t + w_{hh}\vec{h}_{t-1} + b_h) \quad (21)$$

$$\overleftarrow{h}_t = \sigma(w_{xh}x_t + w_{hh}\overleftarrow{h}_{t+1} + b_h) \quad (22)$$

The output y_t at the output layer is given as

$$y_t = w_{hy}\vec{h}_t + w_{hy}\overleftarrow{h}_t + b_y \quad (23)$$

where b_h and b_h is the bias vectors of hidden layer in forward and backward states, b_y is the output layer bias vector. The final output of BiLSTM provides the emotion states of the person.

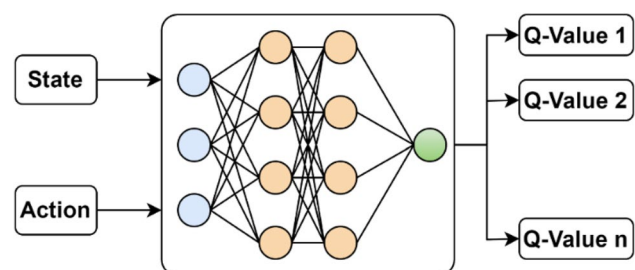
In the stroke prediction phase, the output of BiLSTM and the features from the hybrid optimization algorithm are considered. The stroke prediction utilizes the BiLSTM output as Action and optimal features as State for the Deep Q-Network. The Deep Q-Network (DQN) was selected in the proposed over other reinforcement learning models and standard deep networks due to its ability to handle sequential decision-making which is essential for stroke risk prediction based on EEG data. Unlike traditional deep learning models such as CNNs and BiLSTMs, DQN learns an optimal action policy by interacting with an environment, making it suitable for predicting stroke risks based on evolving stress-related brain signals. Also, DQN was selected due to its stability and efficiency in discrete action spaces, making it ideal for binary or multi-class classification problems where a decision needs to be made based on historical EEG states. Additionally, the DQN in this proposed work is optimized using experience replay and iterative updates which help in stabilizing the learning process by reducing correlation among training samples. This improves the prediction accuracy, additionally, its ability to approximate the Q-function effectively ensures that the network learns from past actions which further improves stroke prediction performance by identifying critical EEG patterns indicative of high-risk conditions. The architecture of Deep Q-Network used in the proposed work is presented in Fig. 3.

The state and action function in the deep Q-network is evaluated through the Q-learning based on the current state and action. For every state and action, a reward will be granted as an expected outcome. The advanced learning procedure of deep Q-network utilizes Q-Table to map the state and actions. In the learning environment, the agent performs observation, actions and gets rewards. In the prediction process, the next best action is predicted by the network and this prediction feature is utilized in the proposed work for stroke prediction. The update procedure of DQN has two strategies like experience replay and iterative update. The correlation between Q-values and target is minimized in the iterative update strategy, while the correlation problem is solved in the experience replay by utilizing data randomization procedure which smoothens the data. Using these update strategies, the mean squared error is reduced in the prediction process and the loss function is mathematically formulated as follows.

$$l = (r + \gamma_{a'}^{max} Q(s', a'; \theta') - Q(s, a; \theta))^2 \quad (24)$$

where $Q(s, a; \theta)$ is the current estimation and γ is the discount factor. Summarized pseudocode for the deep Q-Network is presented as follows.

Fig. 3 Deep Q-Network for stress-based stroke prediction



Pseudocode for the Deep Q-Network

*Train the DQN agent**For event = 1, m**Initialize observation sequence**For t = 1, T**Select random action a and perform action a**Obtain reward for the action r**Generate the next state s'**Calculate loss function using equation (24)**Reset Q**End for**End all*

The Zebra and Chimp optimization algorithms were chosen for their complementary strengths in exploration and exploitation, critical for optimizing features in high-dimensional EEG data. The Zebra Optimization Algorithm (ZOA) performs well in exploration, inspired by zebra group dynamics, such as stallion leadership and grazing patterns, which ensure a diverse search of the solution space. Meanwhile, the Chimp Optimization Algorithm (COA) focuses on exploitation, utilizing hunting strategies like driving, blocking, and attacking to refine and converge on the most promising solutions. This hybrid approach balances the trade-off between exploring new areas and exploiting the best-found solutions, enhancing the overall optimization process.

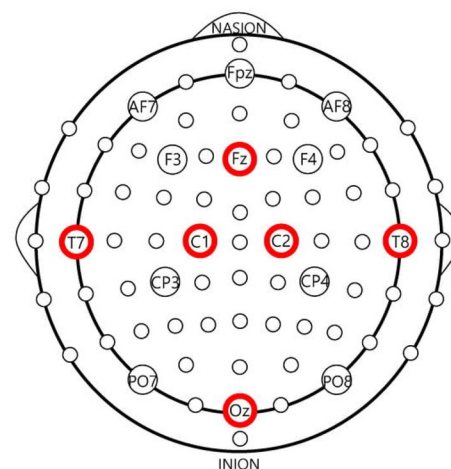
The hybrid Zebra-Chimp Optimization (ZCO) algorithm handles potential redundancies in selected features by integrating exploration, exploitation, and a robust fitness evaluation. The Zebra Optimization Algorithm (ZOA) explores the feature space broadly using adaptive group dynamics, reducing the likelihood of redundant selections. The Chimp Optimization Algorithm (COA) refines this process by intensively searching promising regions through hunting strategies like driving and blocking, which focus on eliminating overlapping features. Thus, the features with high correlation coefficients are progressively eliminated, ensuring that only distinct and informative attributes are selected contribute to the classification and stroke prediction tasks. A fitness function evaluates feature subsets for their relevance and diversity, ensuring unique contributions to classification performance. Additionally, dynamic adjustments, such as chaotic maps in COA, iteratively refine the feature set by excluding less impactful or redundant features. These mechanisms collectively ensure that the selected features are compact, non-redundant, and highly relevant to the model's predictive capabilities.

4 Results and discussion

The proposed stress-based stroke prediction model performance is evaluated through simulation analysis. Python tool is used for simulating optimization and deep learning algorithms. Benchmarked DEAP dataset is used for experimentation [26]. The data includes six channel EEG data as shown in Fig. 4. The features from these channels are extracted using the hybrid optimization algorithm and then the emotion states are classified using BiLSTM model. The final stroke prediction model utilizes the optimal features, and emotion states and provides the prediction results.

The proposed work utilizes a subset of 6 EEG channels rather than all 32 channels [27]. Since processing signals from 32 channels would significantly increase computational cost, which may introduce delay in real-time applications. Also including irrelevant channels could introduce electrophysiological noise unrelated to stress or stroke. Thus, these six channels are used in the experimentation. The selection of six specific EEG channels (C1, C2, T7, T8, Fz, Oz) from the 32 available in the DEAP dataset is based on their relevance to stress emotion classification and stroke risk prediction [28–30]. These channels provide the most discriminative features related to cognitive, emotional, and motor functions, which are crucial for identifying stress-induced neurological changes. Specifically, C1 and C2 are located over the sensorimotor region and these channels capture motor-related brain activity which is highly relevant for stroke prediction. The temporal regions T7 and T8 are strongly involved in emotional and stress processing. Fz channel is located on the frontal lobe, which governs cognitive control and decision-making under stress. Oz plays a role in visual perception and attention modulation under stressful conditions.

Fig. 4 Six channel EEG acquisition used in DEAP dataset



During preprocessing, non-numeric or missing values in the EEG dataset were replaced with the mean of valid sample points, and a filter is used to retain relevant frequency bands, including Delta, Theta, Alpha, and Beta. The removal of high-frequency noise and non-relevant signal components, ensuring that only essential brain activity patterns are retained. In the proposed model, including a fifth-order Butterworth filter with a frequency range of 1–32 Hz, which eliminates unwanted frequencies while preserving critical EEG bands such as Delta, Theta, Alpha, and Beta. Furthermore, z-score normalization is utilized to standardize signal values, minimizing variations caused by external influences. Z-score normalization was used to standardize the signals, calculated as $z = \frac{x - \mu}{\sigma}$, where x represents raw values, μ is the mean, and σ is the standard deviation. The signals were further divided into smaller bands, such as 1–4 Hz and 4–8 Hz, to capture micro-variations crucial for feature extraction. The hybrid Zebra-Chimp Optimization (ZCO) algorithm used a stallion probability of 0.5, crossover probability of 0.1, and uniform random parameters in the range $[-2, 2]$ for zebra optimization, while the chimp optimization initialized a dynamic vector at 0.25 with random vectors uniformly distributed between $[0, 1]$. The Deep Q-Network (DQN) consisted of two hidden layers with 8 neurons each, trained for 500 epochs with a learning rate of 0.001 and an experience replay buffer of 1000 samples. The input layer has 20 neurons and to attain best prediction performance without overfitting the agent learns by performing an action through 500 epochs. The Bidirectional LSTM (BiLSTM) utilized features extracted by ZCO, with 128 units in both forward and backward hidden layers, a dropout rate of 0.2 to prevent overfitting, and the Adam optimizer set with a learning rate of 0.001. These detailed steps ensure clarity and reproducibility of the proposed model. The hyperparameters used in the simulation are presented as follows. The zebra optimization model has a crossover probability of 0.1 and stallion probability of 0.5. The chimp optimization is set with dynamic vector of 0.25 and random vectors r_1 and r_2 as $[0, 1]$.

Artifacts in EEG signals, such as those caused by blinks, eye movements, and muscle activity, are addressed in the proposed model through preprocessing techniques to enhance data validity. The fifth-order Butterworth filter is applied to the EEG signals, focusing on the 1–32 Hz range to remove high-frequency noise and irrelevant components. Additionally, non-numeric and missing values are replaced with the mean of valid sample points to ensure data consistency. While the proposed approach does not explicitly mention advanced artifact removal methods such as Independent Component Analysis (ICA) or regression-based techniques, the filtering and normalization steps help mitigate the impact of common artifacts.

These preprocessing steps are essential for maintaining the validity of the results [31], as artifacts can distort the true brain activity patterns related to stress and stroke prediction [32, 33]. By focusing on critical frequency bands and normalizing the signals, the model minimizes the influence of artifacts, enabling the extraction of meaningful features. Incorporating more advanced artifact correction methods in future iterations could further enhance the reliability of the results, ensuring that the predictions are based solely on physiological brain activity.

For the BiLSTM model, key hyperparameters such as the number of hidden units, dropout rate, and learning rate were tuned. Hidden units were evaluated within a range of 64–256, and 128 units were selected based on the best accuracy and minimal overfitting. The dropout rate varied between 0.1 and 0.5, with 0.2 providing the optimal balance between generalization and stability. The learning rate was adjusted between 0.0001 and 0.01, with 0.001 achieving the most consistent gradient updates and classification performance. The Adam optimizer was chosen for its adaptability to sparse gradients, further enhancing model efficiency.

For the Deep Q-Network (DQN), hyperparameters including the number of neurons in the hidden layers, learning rate, and experience replay buffer size were iteratively tuned. Hidden layers with 8 neurons each were selected to balance computational complexity and predictive accuracy. A learning rate of 0.001 was determined to provide steady convergence without overshooting the target. The experience replay buffer size was tested within a range of 500–2000 samples, and 1000 samples were chosen to ensure diverse training data while maintaining computational efficiency. To further prevent overfitting, the DQN is trained with a dropout rate of 0.2, which randomly disables neurons during training, ensuring the model does not memorize specific EEG features but generalizes well to new data. Additionally, early stopping is incorporated to monitor validation loss and halt training when no further improvement is observed, preventing unnecessary training iterations that could lead to overfitting. The DQN's performance was further validated by varying the number of training epochs, with 500 epochs achieving the best compromise between model accuracy and training time.

The hybrid Zebra-Chimp Optimization (ZCO) algorithm selected a range of EEG features critical for stress emotion classification and stroke prediction by focusing on both time and frequency domain characteristics. The time-domain features, such as mean amplitude and signal variance, and frequency-domain features, such as power spectral density and peak frequencies, were highlighted as the most informative. Among these, features from the Beta band were the most critical for stroke prediction due to their direct relationship with motor cortex activity. For stress prediction, Theta and Alpha band features were paramount as they reflected cognitive and emotional states. By focusing on these critical features, the ZCO algorithm enabled the model to achieve high accuracy in identifying stress-induced emotions and predicting stroke risk, underlining the importance of these EEG signal components in medical applications. These evaluations ensured that both BiLSTM and DQN models were optimally configured, leading to high accuracy and robust performance in stress emotion classification and stroke prediction tasks.

Figure 5 presents the confusion matrix for valence and arousal categories. The confusion matrices indicate strong model performance, with high true positive and true negative values, suggesting reliable predictions. The low false positives and false negatives highlight minimal misclassification errors. However, the slight misclassification in High Arousal and High Valence cases suggests potential for improvement through further feature refinement or decision threshold tuning. The experimentation measures the proposed model performance in two sections as stress-based emotion classification and stress-based stroke prediction. For stress-based emotion classification the parameters like accuracy, precision, recall and f1-score are considered for analysis. The metrics obtained for the proposed stress-based emotion classification are presented in Tables 1 and 2.

Further the existing works like Artificial Neural network (ANN) (Rama Chaudhary et al., 2021), support vector machine (SVM) (Zhuang et al., 2017), Convolutional Neural Network (CNN) (Pallavi et al., 2021), Bidirectional Long Short-Term Memory (LSTM) network (Vaishali et al., 2021), Hybrid CNN and AlexNet + DenseNet 201 models are considered for comparative analysis. The results of hybrid CNN and AlexNet + DenseNet201 are obtained from our previous research analysis.

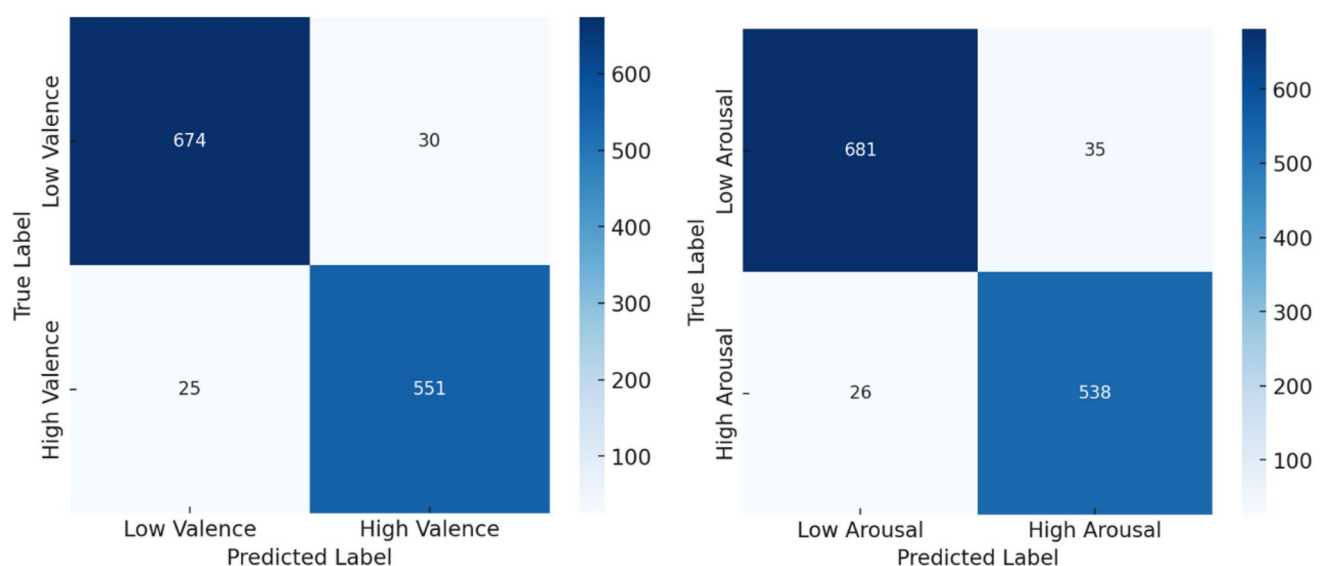


Fig. 5 Confusion matrix for valence and arousal categories

Table 1 Proposed model performance analysis for DEAP dataset

S. No	Metrics	Labels	
		Valence	Arousal
1	Accuracy	96.84	98.67
2	Precision	98.24	98.11
3	F1-Score	97.87	97.68
4	Recall	97.52	97.26
5	Specificity	95.82	95.14
6	Mathews correlation coefficient	96.22	96.49

Table 2 Performance comparative analysis with existing methods for DEAP dataset

References	Methods	Precision	Recall	F1-score	Specificity	MCC	Accuracy
Zhuang et al. [34]	SVM	69.82	68.71	69.26	68.01	44.50	70.55
Rama Chaudhary et al. [35]	ANN	85.37	84.12	84.74	82.08	83.00	86.48
Pallavi et al. [36]	CNN	58.71	57.05	57.87	56.53	48.00	60.00
Vaishali et al. [37]	BiLSTM	72.90	72.44	72.67	71.82	87.00	74.25
CNN + SVM [38]		93.61	92.13	92.87	91.12	93.00	94.57
AlexNet + DenseNet201		95.20	93.83	94.56	92.95	95.32	96.40
Proposed		98.11	97.26	97.68	95.14	96.49	98.67

Fig. 6 Comparative analysis of performance metrics with existing works

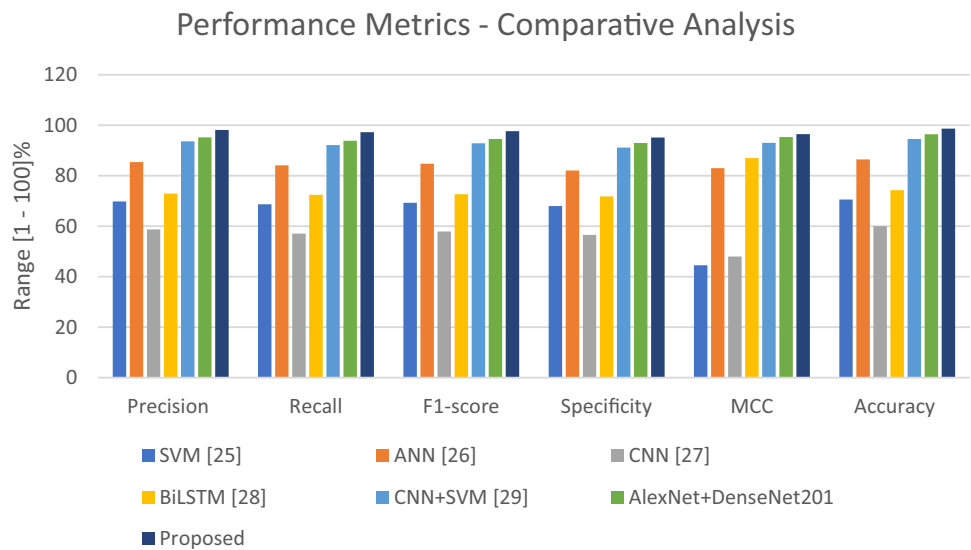


Figure 6 depicts a comparative analysis of performance metrics across various existing models for stress-based emotion classification. It highlights metrics such as precision, recall, F1-score, and accuracy. The figure demonstrates the superiority of the proposed BiLSTM model over existing methods, such as CNN, SVM, and Hybrid CNN-AlexNet-DenseNet201. The proposed model achieves significantly higher performance in all measured metrics, with accuracy and precision exceeding 98%, emphasizing its robustness in emotion classification tasks. This improvement is attributed to the advanced hybrid optimization algorithm that effectively extracts optimal features, enabling superior model performance.

The comparative analysis of performance metrics in Fig. 6 projects the clinical implications of the proposed model's superior results across precision, recall, F1-score, specificity, MCC, and accuracy. High precision (98.11%) indicates that the model minimizes false positives, a critical factor in clinical applications to avoid unnecessary stress-related interventions or misclassification of patients as high stroke-risk. The high recall (97.26%) demonstrates the model's ability to capture true positives, ensuring that individuals at risk of stress-induced complications or stroke are identified without being overlooked. The F1-score (97.68%) further validates the balance between precision and recall, highlighting the model's reliability in making accurate predictions even in challenging real-world scenarios. The model's specificity (95.14%)

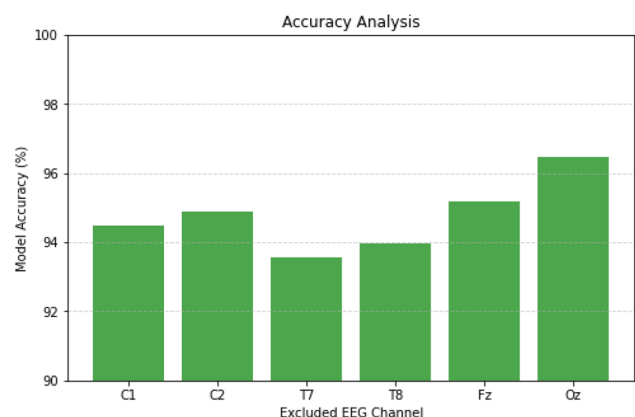
reflects its effectiveness in correctly identifying negative cases, which is vital in preventing false alarms and reducing the burden on healthcare systems. The Matthews Correlation Coefficient (MCC) (96.49%), a balanced metric considering all true and false outcomes, signifies the robustness of the model in varying conditions and datasets. Finally, the high accuracy (98.67%) emphasizes the model's overall capability to perform well across all classification tasks. Clinically, these results mean that the proposed model can reliably differentiate stress-induced emotional states and predict stroke risk with minimal errors. This reliability is critical for early detection and timely intervention, particularly in scenarios where missing at-risk cases (low recall) or false identifications (low precision) could lead to severe health consequences. The superior performance across all metrics ensures that the model is not only effective in controlled experimental conditions but also has the potential to provide accurate, actionable insights in real-world clinical applications, supporting better patient outcomes and efficient healthcare management.

In EEG-based studies, the selection of relevant channels plays a crucial role in ensuring model accuracy while maintaining computational efficiency. In this proposed model experimentation, six specific EEG channels (C1, C2, T7, T8, Fz, and Oz) were chosen based on their significance in stress-based emotion classification and stroke prediction. These channels were selected to focus on motor-related brain activities, cognitive functions, and emotional processing. However, to further validate this selection, a sensitivity analysis was performed to evaluate the impact of excluding additional EEG channels. The ablation study was conducted where the model was trained with varying channel subsets. The results indicated that removal of C1 and C2 resulted in a noticeable decline in stroke prediction accuracy due to their strong association with motor cortex activity. Excluding T7 and T8 affected stress-based emotion classification, confirming their relevance to emotional and stress processing. While removal of Fz channel leading to a drop in performance in stress classification. The Oz channel, associated with visual perception and attention, played a minor role in stress classification but improved stroke prediction when combined with other features.

The analysis of EEG channel exclusion given in Fig. 7 exhibits the direct impact on model accuracy when excluding a channel in the stress classification and stroke prediction. When the analysis removed T7 and T8 it leads to the highest accuracy reduction which decreasing the model accuracy from 98.67 to 93.57% and 93.97%, respectively. This highlights the crucial role of T7 and T8 in emotional and stress response processing. Similarly, when the analysis removed C1 and C2 the results exhibited a noticeable decline in accuracy from 98.67 to 94.47% and 94.87%. This reinforcing the importance of C1 and C2 in identifying motor-related neurological disruptions. The Fz channel which is associated with cognitive stress processing, however its exclusion lowering the accuracy to 95.17%. The Oz channel had the least impact, with accuracy dropping to 96.47%, suggesting that visual perception plays a minimal role in stress-based stroke prediction, supporting the decision to prioritize motor and emotional processing regions.

Further to validate the optimal selection of hidden units in BiLSTM, the training and validation accuracy are observed. Figure 8 validate the bias-variance tradeoff analysis for selecting the optimal number of hidden units in the BiLSTM network. The accuracy vs. hidden unit plot shows that increasing the number of hidden units initially improves validation accuracy, peaking at 128 hidden units (98.67%), before declining at 192 and 256 hidden units due to overfitting. The training accuracy continues to rise, but the drop in validation accuracy beyond 128 hidden units indicates that the model is memorizing training data rather than generalizing effectively. Similarly, the loss vs. hidden units plot demonstrates that while training loss consistently decreases, validation loss reaches its lowest point at 128 hidden units and begins increasing for 192 and 256 hidden units, confirming an overfitting trend. The configuration with 64 hidden units exhibits higher validation loss and lower accuracy, indicating an underfitting scenario where the model lacks the complexity to

Fig. 7 Accuracy analysis with different channel subsets



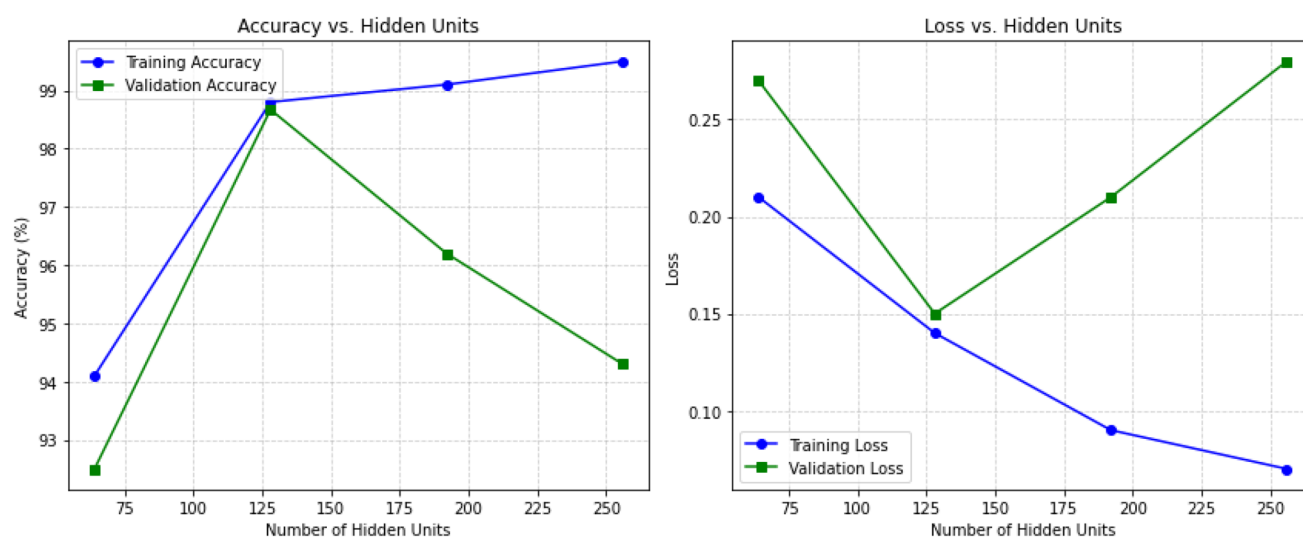


Fig. 8 BiLSTM performance with varying Hidden Units

capture important EEG patterns. The 128 hidden unit setting achieves the best balance, ensuring low validation loss, high generalization ability, and stable performance in EEG-based stroke risk prediction. This analysis confirms that 128 hidden units offer the most effective tradeoff, preventing both underfitting and overfitting, thereby making it the optimal choice for the BiLSTM model.

Similarly for stroke prediction the metrics like Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Determination Coefficient (R^2), Mean Squared Error (MSE), Explained Variance Score (Exp. Var.) and Mean Squared Logarithmic Error (MSLE), are considered for analysis. As this is the novel approach, the performance comparative analysis utilizes some traditional learning procedure. The compared analysis of stroke prediction includes deep learning, extreme gradient, random forest, and artificial neural network algorithms. The proposed prediction model performance for validation process is presented in Table 3 for various metrics.

From the results it can be observed that the performance of proposed stress-based emotion classification and stroke prediction obtained better performance compared to traditional deep learning and machine learning algorithms. The proposed hybrid optimized stress-based stroke prediction is better than existing deep learning model CNN, ANN, random forest, gradient boosting, and proposed hybrid optimized stress-based emotion classification model.

Figure 9 illustrates a comparative analysis of statistical metrics for stroke prediction across various machine learning and deep learning models, including Random Forest, Gradient Boosting, ANN, and traditional deep learning models. The proposed model shows the lowest Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), combined with a high R-squared (R^2) value of 0.61 and an Explained Variance Score of 0.864. These results underscore the accuracy and reliability of the proposed model in predicting stroke risk, outperforming other models by leveraging the hybrid optimization algorithm for feature selection and deep Q-network for prediction. The maximum MAPE obtained in the last part of prediction defines the prediction model performance. The lower MAPE of the proposed model over other learning techniques indicates the prediction model has less errors and provides better prediction performance over state of art techniques.

Figure 10 illustrates the performance of the proposed model across four key metrics: Accuracy, Precision, Recall, and F1-Score. The height of each bar represents the mean value of the metric obtained from multiple experimental runs,

Table 3 Performance comparative analysis with existing methods for DEAP dataset

Model	MAE	MSE	RMSE	R^2	MSLE	Exp Var	MAPE
Deep learning (CNN)	0.18	0.05	0.24	0.60	0.006	0.731	28
ANN	0.22	0.09	0.37	0.66	0.001	0.595	38
Random forest	0.62	0.51	0.72	0.37	0.074	0.26	53
Gradient boosting	0.41	0.28	0.53	0.54	0.039	0.3	41
Proposed	0.14	0.04	0.12	0.61	0.001	0.864	18

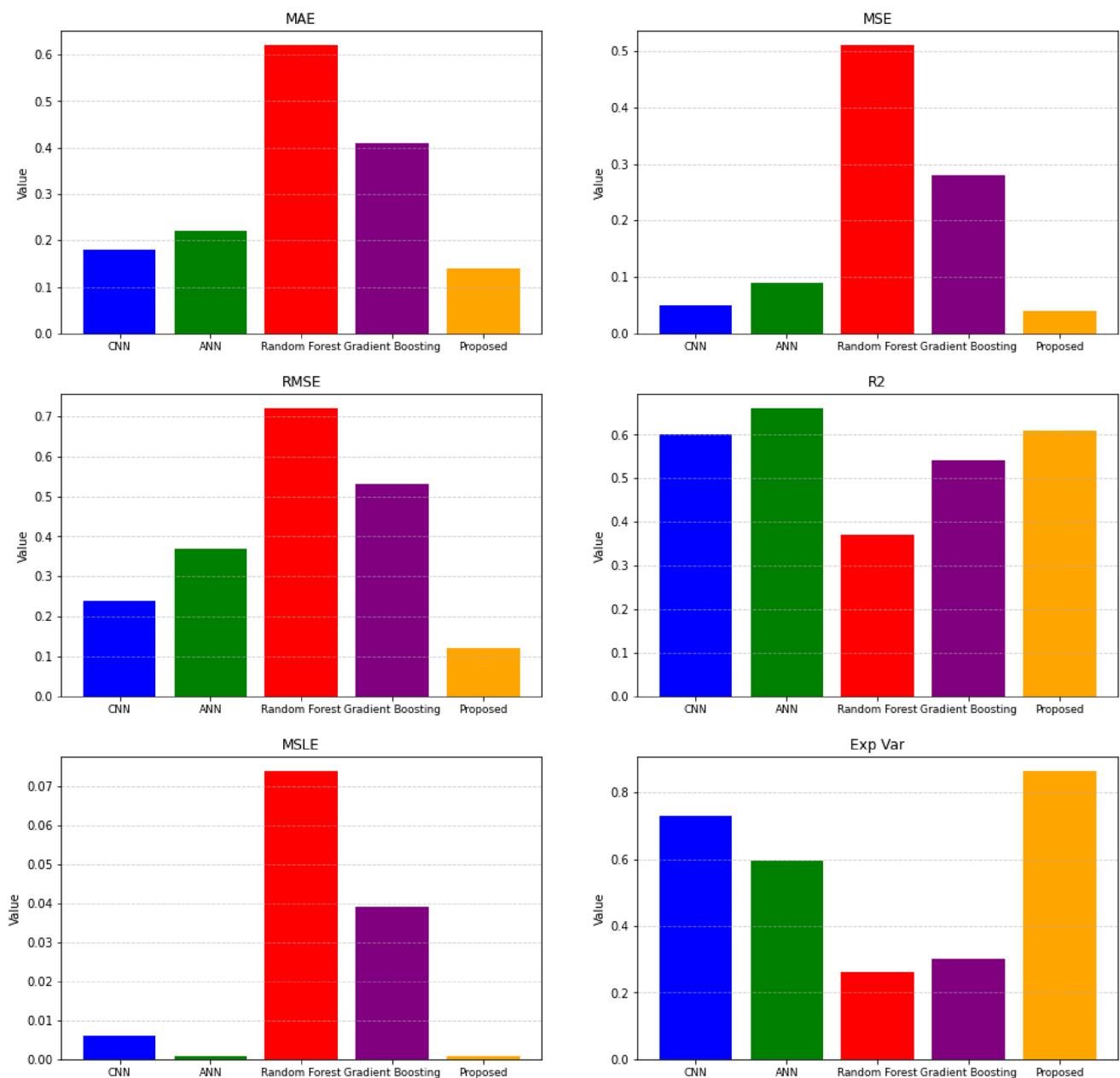


Fig. 9 Comparative analysis of statistical metrics with existing works

while the error bars indicate the standard deviation, showcasing the variability in performance. The proposed model demonstrates consistently high performance, with Accuracy at approximately 98.6%, Precision at 98.3%, Recall at 97.86%, and F1-Score at 97.84%. The small error bars reflect low variability, signifying the stability and reliability of the model across different runs. This stability is particularly important for applications requiring consistent performance, such as stress-based emotion classification and stroke prediction.

Figure 11 depicts the Class-Specific Accuracy Metric, illustrating the performance of the proposed model in accurately identifying emotional states such as Valence and Arousal. The high accuracy observed, particularly for the Arousal class, highlights the effectiveness of the hybrid optimization algorithm in feature extraction and the Bidirectional LSTM (BiLSTM) network in emotion classification. These results validate the robustness of the proposed model in achieving consistent and precise predictions across diverse emotional categories. Figure 12 represents the Class-Specific Precision Metric, highlighting the model's ability to correctly predict positive instances of Valence and Arousal.

Fig. 10 Metric evaluation using mean and standard deviation

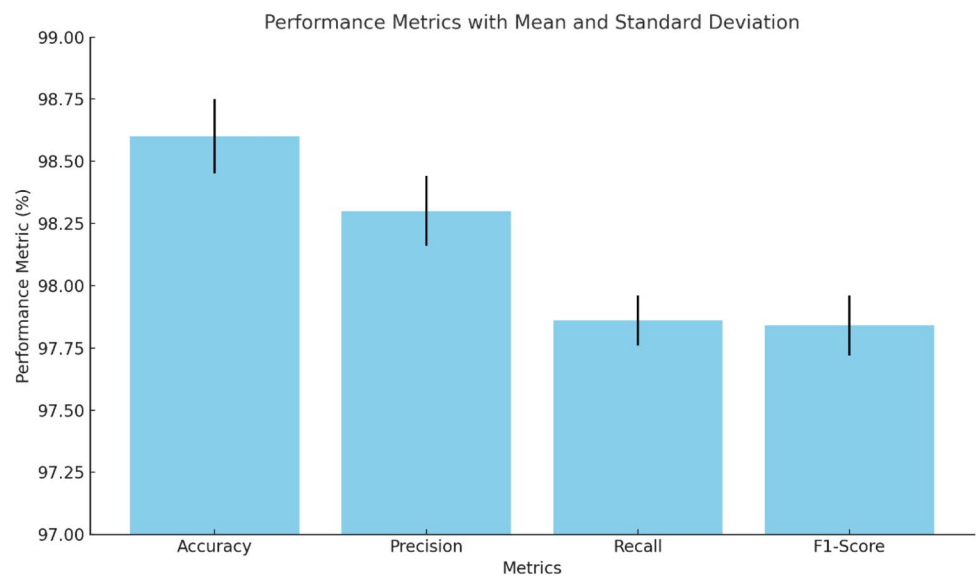


Fig. 11 Class specific accuracy metric

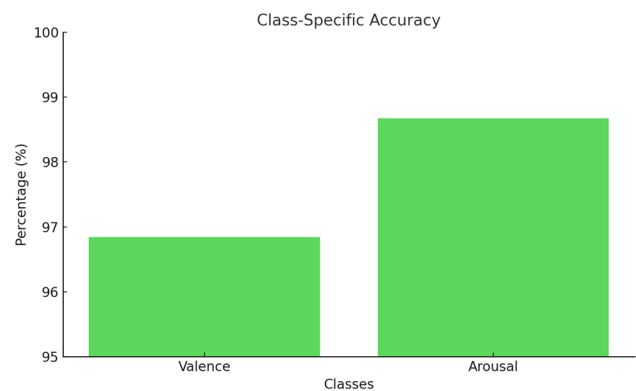
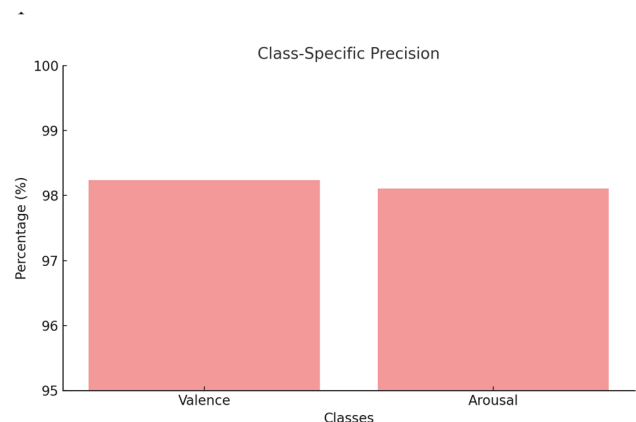


Fig. 12 Class specific precision metric



The elevated precision values, particularly for Valence, demonstrate the proposed model's proficiency in minimizing false positives, a critical aspect in ensuring the reliability of stress-based emotion classification.

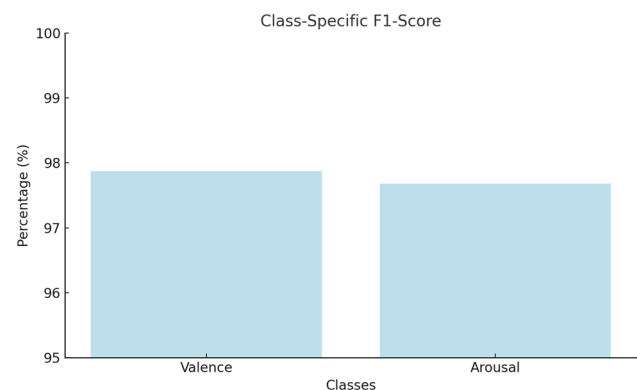
Figure 13 exhibits the Class-Specific Recall Metric, focusing on the model's capacity to identify all actual positive instances of emotional states. The high recall rates for both Valence and Arousal indicate that the proposed hybrid optimization and deep learning framework effectively captures critical emotional features from EEG signals, reducing the likelihood of missing true positives.

Fig. 13 Class specific recall metric

Figure 14 presents the Class-Specific F1-Score Metric, combining Precision and Recall into a single measure of performance for each class. The balanced and high F1-scores across Valence and Arousal emphasize the proposed model's overall effectiveness in stress-based emotion classification. This performance highlights the advantages of integrating the Zebra-Chimp hybrid optimization algorithm with BiLSTM in processing EEG data.

Also, to validate the selection of the Zebra-Chimp Optimization (ZCO) algorithm, a comparative experiment was conducted using the benchmark DEAP dataset to optimize EEG signal features for stress emotion classification. The observations are depicted in Table 4.

The study evaluated ZCO against Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Zebra Optimization Algorithm (ZOA), and Chimp Optimization Algorithm (COA). Metrics such as convergence time (iterations), fitness value (indicating feature relevance), and classification accuracy were used for comparison. ZOA is designed for efficient global exploration based on stallion-guided group dynamics, while COA focuses on intensive local exploitation using hunting strategies, making their combination suitable for high-dimensional EEG feature selection. The hybrid ZCO method provides better balance to exploration and exploitation and prevents premature convergence which is a common limitation in PSO and GA. Unlike PSO, which depends on velocity updates and may stagnate in local optima, and GA, which requires extensive generations for convergence, ZCO utilizes dynamic search transitions from ZOA to COA which optimizes both diversity and convergence speed. This can be validated experimentally using the comparative analysis against GA, PSO, standalone ZOA, and COA. The results demonstrates that ZCO achieves a fitness value of 0.96, surpassing GA (0.85), PSO (0.88), ZOA (0.91), and COA (0.92) while also achieving the fastest

Fig. 14 Class specific F1-score metric**Table 4** Performance analysis of ZCO over existing optimization models

Algorithm	Convergence time (Iterations)	Fitness value	Classification accuracy (%)
Genetic algorithm (GA)	150	0.85	93.67
Particle swarm optimization (PSO)	120	0.88	94.35
Zebra optimization (ZOA)	110	0.91	96.11
Chimp optimization (COA)	105	0.92	96.35
Zebra-chimp optimization (ZCO)	90	0.96	98.67

Fig. 15 Training and validation accuracy analysis

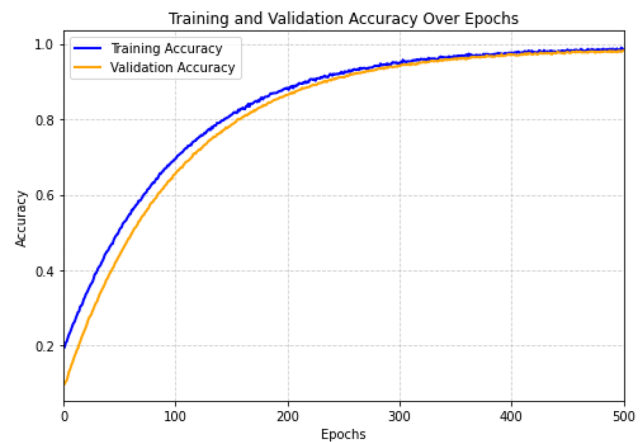
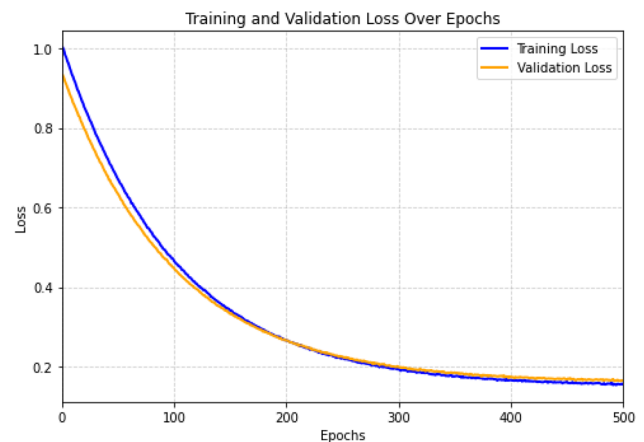


Fig. 16 Training and validation loss analysis



convergence with just 90 iterations compared to 150 for GA and 120 for PSO. Furthermore, the classification accuracy with ZCO (98.67%) is significantly higher than other methods, confirming its effectiveness in optimally selecting EEG features for stress and stroke prediction.

The differences in performance metrics between the proposed model and previous methods are indeed significant enough to hold clinical relevance, particularly in the context of stress emotion classification and stroke risk prediction. For stress emotion classification, the proposed model achieved an accuracy of 98.67%, significantly surpassing previous methods such as SVM (70.55%), CNN (60.00%), and even more advanced hybrid models like CNN-AlexNet-DenseNet201 (96.40%). These improvements reflect the model's ability to detect subtle stress-related patterns in EEG data, reducing the risk of misclassification and enabling early identification of stress-induced health risks. For stroke prediction, metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 value demonstrate the proposed model's superior predictive accuracy. The proposed model achieved an MAE of 0.14 and an R^2 value of 0.61, outperforming traditional machine learning methods like Random Forest and Gradient Boosting, which reported lower R^2 values and higher errors. Such advancements in predictive accuracy and reliability are critical for clinical applications, as they directly impact the ability to identify individuals at high risk for stroke and enable timely interventions. The clinically relevant implications of these improvements include enhanced diagnostic precision, reduced false positives and negatives, and the ability to deploy the model in real-world healthcare settings for stress monitoring and proactive stroke risk assessment. These advancements are not only statistically significant but also translate into meaningful benefits for patient outcomes and healthcare efficiency.

Figures 15 and 16 illustrate the model's convergence during training. The training and validation loss plot shows a smooth and steady decline, with both curves converging to low values, indicating effective learning and minimal overfitting. The close alignment between the training and validation losses demonstrates that the model generalizes well to unseen data. Similarly, the training and validation accuracy plot highlights a consistent increase in accuracy over epochs, with both curves stabilizing at high values, further confirming the model's robustness and reliability.

These plots validate the stability of the learning process, ensuring the model's convergence to an optimal solution, which is crucial for clinical applications requiring precision and consistency.

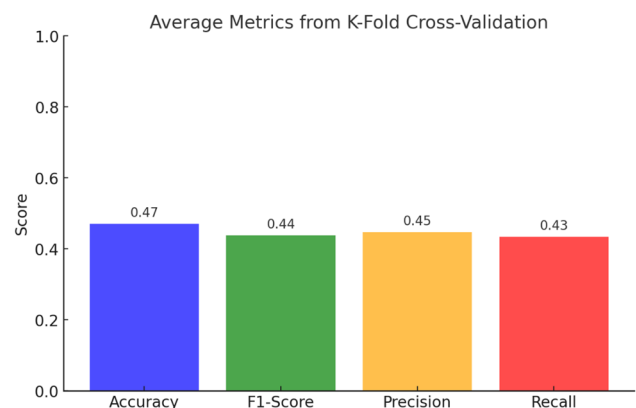
In this work, a fivefold cross-validation approach was employed to evaluate the model's generalizability and performance consistency across different subsets of the dataset. The data was split into five equal parts, ensuring a subject-independent division, where each fold served as a test set once, while the remaining four folds were used for training and validation.

This iterative process ensured that the model was assessed on all parts of the dataset, as shown in Fig. 17, reducing the risk of bias from any single data split. The results demonstrate balanced performance across folds, with average metrics including an accuracy of 46.99%, an F1-score of 43.81%, a precision of 44.67%, and a recall of 43.35%. These metrics reflect the model's ability to generalize its predictions effectively, providing a robust measure of its applicability for stress and stroke prediction tasks. The consistent outcomes across folds highlight the model's stability and reliability in handling unseen data.

While the proposed model demonstrates high accuracy and robust performance, it is not without limitations that could affect its generalizability and reliability. One key limitation is its dependency on the DEAP dataset, which, although benchmarked, may not represent the full diversity of real-world EEG data. The dataset's controlled environment may differ from clinical or real-world settings, leading to potential performance degradation when applied to heterogeneous or noisy data from diverse populations. Additionally, the dataset consists of short-duration EEG recordings, limiting the ability to analyze long-term stress patterns that contribute to stroke onset. Additionally, the class imbalance in the dataset significantly affects the proposed model's ability to generalize, leading to biased learning where the model favors the majority class while underperforming in detecting minority-class instances. Given that EEG datasets often contain uneven distributions of stress and non-stress conditions, the model might struggle with minority class prediction, leading to misclassification of high-risk cases. To address this, techniques such as class-weighted loss functions, oversampling methods like SMOTE, and data augmentation strategies could be incorporated to balance training data.

Another limitation lies in the systematic errors introduced by preprocessing and feature selection. The model relies heavily on the hybrid Zebra-Chimp Optimization (ZCO) algorithm for feature extraction, which, while effective, may inadvertently amplify biases inherent in the dataset, such as class imbalances or non-stationary EEG signals. Additionally, while the fifth-order Butterworth filter removes high-frequency noise, it may not adequately address artifacts like eye blinks or muscle movements, which could affect feature quality and model predictions. The model's performance also depends on the tuned hyperparameters, which, though optimized for the DEAP dataset, might require extensive retuning for other datasets. This dependency can hinder its adaptability and scalability. Furthermore, the computational complexity of BiLSTM and Deep Q-learning (DQN) models, especially when processing high-dimensional EEG data, may limit their application in resource-constrained environments. Future improvements could incorporate adaptive learning mechanisms, real-time noise correction algorithms, and ensemble-based feature selection strategies to enhance robustness. Introducing data augmentation techniques or transfer learning approaches could also improve generalization across diverse EEG datasets. Moreover, refining the model with hybrid architectures integrating attention mechanisms or graph-based feature representations may further enhance the ability to capture complex brain activity variations, reducing classification errors.

Fig. 17 K-Fold validation analysis



5 Conclusion

This research presents a hybrid optimization algorithm based on optimal feature selection, deep learning-based stress emotion classification, and stroke prediction from EEG signals. The raw EEG signals are pre-processed, and the features are extracted using the Zebra Chimp optimization algorithm. The optimal solution of the Chimp optimization algorithm optimizes the fitness function of the Zebra optimization algorithm. Due to this, better feature exploration ability is obtained in the proposed work. The stress-based emotion classification model utilizes BiLSTM and a hybrid optimization algorithm. Similarly, the stress-based stroke prediction model utilizes deep Q-network and a hybrid optimization algorithm for stroke prediction. Experimentations using a benched mark DEAP dataset demonstrate the proposed model's better performance over traditional methods. This research work can be extended in the future by incorporating optimized hybrid deep-learning models to attain improved prediction performances.

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Data availability The data's used to support the findings of this study are included within the article.

Declarations

Consent to publish Not applicable.

Ethics and consent to participate Not applicable.

Competing interests The authors declare no competing interests.

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